Ensemble One-vs-One SVM Classifier for Smartphone Accelerometer Activity Recognition

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***Abstract*—A recognition framework to identify six full body motion from smartphone sensory data is proposed. The proposed system relies on accelerometer, gyroscope and magnetometer data to classify user activities into six groups (sitting, standing, lying down, walking, walking up stairs and walking downstairs). The proposed solution is an improvement of a one-verse-one SVM classifier with an ensemble of different learning methods each trained to discriminate a single activity against another. The improvement presented here doesn't only focus on accuracy but also potential embedded implementation capable of performing real-time classification with mobile data from the cloud. The presented one-versus-one approach, based on a linear kernel achieved 97.50 percent accuracy on a public dataset; second best to 98.57 percent reported in literature which uses a polynomial kernel.**

***Keywords*-Smartphone Accelerometer Data; Support Vector Machine; One-versus-One ensemble; Neural Network**

I. Introduction

Assistive care is a real issue as the world's population age 65 and older is growing by an unprecedented rate. In order to help the elderly with their everyday activities, many innovative approaches to support and offer them with care services have been created [1]. Activity recognition has major applications in healthcare, exercise tracking and wearable technologies [2]. Generally, to collect data for activity recognition, two popular approaches (environmental and wearable sensors) are used, each with its own advantages and disadvantages. Wearable devices including monitoring systems like the iLife fall detection sensors[3] [4] which recognises and reacts to falls, the Health buddy [5] which measures and records vital signs and PROACT [6] glove which monitors contact with everyday objects, are becoming increasingly useful in health provision.

Today's mobile devices, such as cellular phones and music players incorporate diverse and powerful sensors [2] including GPS, audio, image, light, temperature and acceleration sensors. Taylor *et al* [2] demonstrates the use of wearable devices for accelerometer data collection and how such data can be used for cloud-based activity monitoring is also presented in [7]. In general, interpreting the massive amount of data that every cloud-connected object records is challenging, but when managed in real-time it can be useful for assistive care.

Human activities have been classified into three main types in [8] as short event, basic and complex activities. To classify such activities, many methods have already been used [9], like the generic architecture for big data healthcare analytic [10], Map Reduction [11], Nave Bayes [12] and Machine Learning (ML) [13]. Each of these methods dominate in different application areas, but machine learning is most suited for tasks like the one in [14], which involves activity classification [15]. Machine learning also offers different approaches capable of activity classification in real-time once the model is trained. Real-time machine learning approaches may include Support Vector Machine (SVM)[16], k-nearest neighbours (KNN) [17][18] and random forest (RF) [19].

This paper focuses on the use of SVM, random forest and discriminant analysis simultaneously in a one-versus-one approach to classify six daily activities (sitting, standing, lying down, walking, walking up stairs and walking downstairs) captured from the accelerometer of a smartphone. The presented approach has been carefully engineered for a possible real-time Field Programmable Gate Array (FPGA) implementation. The rest of the paper is organised as follows, section II presents work related to our proposed classifier, this is followed by details of our approach including the Human activity recognition (HAR) dataset [20] and features used in section III-A, the challenges related to the dataset and how it has motivated us in section III-B, and also details of our classifier in section III-C. The experimental and evaluation results are presented in section IV, which is followed by conclusion and future work in V.

II. Related work

Some work on data classification has already been done on the dataset introduced in 2012 by Anguita *et al*[20]. Three different method with good results were introduced as part of the original competition for the [20] HAR dataset in 2013[21]. The first of the three is the one-versus-one (OVO) multi-class SVM with linear kernel proposed by Romera-Paredes *et al* [22] and consists of an ensemble of linear SVM each trained to discriminate a single motion activity against another. Their method [22] used a majority voting to find the most likely activity for each test sample from an arrangement of six binary classifiers and obtained an accuracy of 96.40% with the HAR dataset [20]. For comparative purposes, the work in [22] also evaluated the performance of a six-winner-take-all SVM and a KNN model which exhibited poorer accuracies of 93.70% and 90.60% respectively, compared to what was reported in literature prior to the year 2013.

Kastner *et al* [23] presented the second of the three solutions by applying a kernel variant of learning vector quantization with metric adaptation using only one prototype vector per class. The approach presented in [23] applied the kernelised matrix Generalized Learning Vector Quantization (kGMLVQ), which is a combination of SVMs (kernel mapping) and Generalized Learning Vector Quantization to classify accelerometer data. The implementation using the Kernel variant of learning vector quantization with metric adaptation [23] obtained an accuracy of 96.23%.

Reiss *et al* [24] presented the third and final solution by introducing a new, confidence-based boosting algorithm called ConfAdaBoost.M1, which obtained an accuracy of 94.33% on the same HAR dataset. The ConfAdaBoost.M1 algorithm is a confidence-based extension of the AdaBoost.M1 algorithm. It is a direct multi-class classification technique, using information about how confident weak learners are, in the prediction of the instance's classification and also uses confidence information in both training and testing.

Nurhanim *et al* [8] used the HAR dataset [20] to compare the performance of different kernel of classification for support vector machine. Two approaches were presented, the multi-class support vector machine polynomial kernel and multi-class support vector machine Linear Kernel using "winner take all". Even though, the results of using the one-versus-all or "winner take all" produced remarkable results; 98.57% for the polynomial kernel and 97.04% for the linear kernel, Kane *et al* [25] points out usefulness for a one-versus-one multi-class SVM for real-time FPGA implementation, as it requires minimal on-board memory during training.

Kane *et al* [25] proposed the first ever fully pipelined, floating point based, multi-use reconfigurable hardware architecture designed to act in conjunction with embedded processing as an accelerator for multi-class SVM classification. Their implementation show the benefits of one-versus-one against one-versus-all for real-time applications. This same point was apparent in the work by Sirkunan [26], which proposed a parameterisable linear kernel architecture that is fully pipelined and implemented on Altera Cyclone IV FPGA platform. Further analysis on implementation in [26] determined the effect of the number of features and support vectors on the performance of a hardware architecture.

The approach used in this work is motivated by the one-versus-one multi-class linear SVM with majority voting presented in [22] and it's efficient implementation for real-time applications as presented in [25]. Most of the reviewed implementations focus more on improving the accuracy of the classifier with little or no consideration of real-time implementation, which is mostly needed for assistive care.

III. Our Approach

A. Dataset and Features

For fair comparison, which eliminate any form of bias conclusion, the dataset used to test our classifier comes from the UCI machine learning repository [27]. The data was collected from a group of 30 volunteers between the ages of 19 and 48 years. Each volunteer performed all of the six activities (walking, walking upstairs, walking downstairs, sitting, standing and laying), with a Samsung galaxy S2 smartphone strapped to their waits. The data was captured from the embedded accelerometer and gyroscope to provide the 3-axial linear acceleration and 3-axial angular velocity at a constant rate of 50Hz. The experiments [27] were also video-recorded to make manual labelling of the data easier. To account for training and testing, they [27] have randomly partitioned the dataset into two, with 70% of the volunteers selected for the training data and the other 30% grouped as the test data.

The sensor signals both accelerometer and gyroscope have been pre-processed by applying noise filters and then sampled in fixed-width sliding windows of 2.56 sec and 50% overlap (128 readings/window). The sensor acceleration signal, which has gravitational and body motion components, has also been separated using a Butterworth low-pass filter [28] into body acceleration and gravity. The gravitational force is assumed to have only low frequency components, therefore a filter with 0.3 Hz cut-off frequency was used in [27]. From each window, a vector of features was obtained by calculating variables from the time and frequency domain. Thus for 2.56 seconds of activity, the dataset [27] had 10,299 samples represented as 561 features. Table I provides some of the features included in the dataset and extracted from the time and frequency domain for each window.

Table I
A LIST OF SOME OF THE 561 FEATURES EXTRACTED FROM EACH WINDOW.

Feature	Description
SMA	Signal magnitude area
Min	Smallest value in array
Max	Largest value in array
Std	Standard deviation
Energy	Energy measures.
Iqr	Interquartile range
Skewness	Skewness of the frequency domain signal
Kurtosis	Kurtosis of the Frequency domain signal
Entropy	Signal entropy
arCoeff	Auto regression coefficient
maxFreqInd	largest magnitude frequency component
meanFreq	Weighted average of the frequency component
energyBand	Energy of a frequency interval within the 64bins of the FFT of each window
Correlation	Correlation Coefficient
angle	Angle between two vectors

B. Challenges and Motivation

To understand the structure of the dataset presented in [27], we focussed on the most appropriate way to visualise the features and how easily they can be partitioned. The labelled features have been used to visualise the data in order to identify the key part of the dataset (see figure 1) and also to provide a better picture of the most suitable classifier capable of grouping the various activities in [27]. The graph in figure 1 represents all the six activities in the plan composed of the two principal components and three clusters can easily be identified. The three main groups from figure 1 are:

- the laying activities (in orange)
- the three walking activities (in blue, aqua green and pink)
- the sitting and standing activities (in yellow and green respectively)

From figure 1, it becomes clear that the laying activity is distinctive from all the other activities; the features collected when laying cluster in one area with no overlap. The standing and sitting activities will require a good classifier, if details of the kind of walking being performed by the user isn't needed. The most challenging aspect of the data is the ability to distinguish between all the three walking activities (walking, walking upstairs and walking downstairs) as well as drawing a clear distinction between sitting and standing. After the visual inspection of the labelled data as shown in figure 1, similar to that projected in [22] and shown in figure 2, we opted to apply the one-versus-one model [22]; as it is capable of training to separate a single class amongst all others with less complexity. The one-versus-one strategy is much faster and more memory efficient that the one-versus-all [29]. One-versus-one requires $O(N2)$ classifiers instead of O(N), but each classifier is (on average) much smaller. If the time to build a classifier is super-linear in the number of data points (like the smartphone data used in this paper), then one-versus-one is a better choice and more importantly for a parallel FPGA implementation.

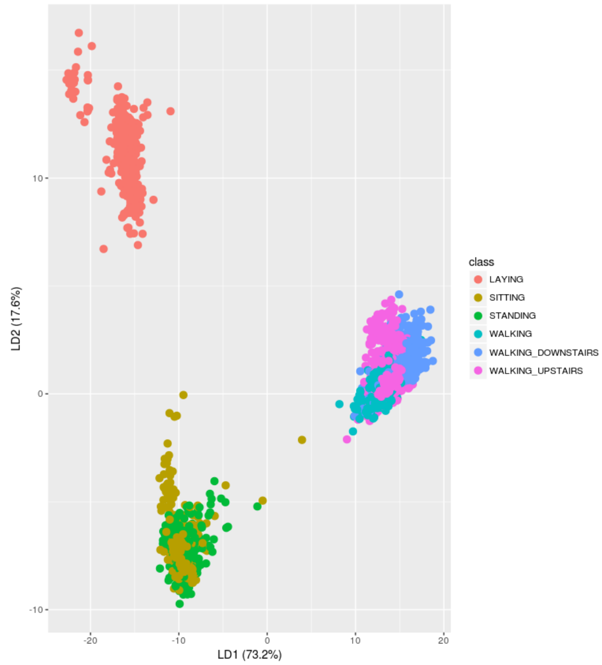

Figure 1. Visual representation of the six activities from the UCI dataset [27].

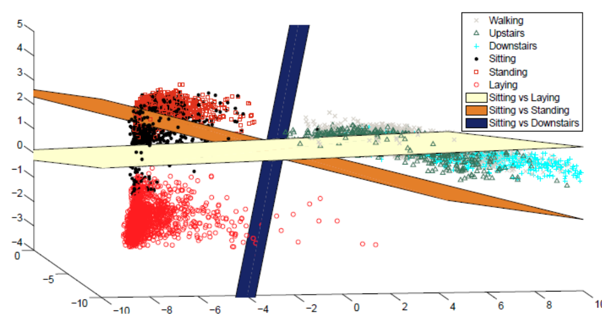

Figure 2. Visual representation of the six activities with three one-versus-one decision boundaries [22].

After choosing an appropriate model capable of distinguishing between classes, various classifiers including SVM, random forest and Linear discriminant analysis (LDA) were applied to determined the most suitable discriminant for the dataset [27]. Preliminary tests were conducted to test the robustness of the three chosen classifiers, table II shows how they perform on the dataset.

Each value in table II considers both the precision and recall of the corresponding test. The LDA is the best within the walking activities but it tends to be the worse amongst the three classifiers when it comes to classifying sitting and standing, because of it's low accuracy levels as shown in table II. The random forest is exactly the opposite of LDA, whereas the SVM is average for each activity group. The

Table II
A MEASURE OF ACCURACY FOR THE THREE SELECTED CLASSIFIERS.

Method comparison (F-score for each label)			
	SVM	Random forest	LDA
Walking	93.9%	91.5%	**98.2%**
Walking downstairs	94.7%	93.7%	**96.6%**
Walking upstairs	95.5%	91.2%	**98.3%**
Sitting	94.5%	**96.2%**	91.7%
Standing	93.8%	**95.9%**	92.9%

preliminary results in table II motivated our choice for using the three classifiers in our one-versus-one model.

C. The Classifier

The proposed system consists of 45 single class classifier, 15 random forests of 300 trees, 15 soft margin linear support vector machines and 15 linear discriminant analysis each trained on a subset of the dataset composed of two classes a and b, described as follows :

$$D_{a,b} = \left\{ (x_i, y_i) | x_i \in \mathbb{R}^p, y_i = \begin{array}{ll} 0 & if \quad class(x_i) = a \\ 1 & if \quad class(x_i) = b \end{array} \right\}_{i=1}^{n}$$

Where p is the number of features and p=561 is used, representing the full set of features provided by the database [27]. x_i is the vector of features for the instance i and n is the number of training instances, determined by the number of instances that belong to class a or b from the N training instances available for all the classes.
Each of the classifiers generates an output decision based on the follow equation:

$$out_i = (A, \alpha_{A,i})$$

A is the class (activity) that the classifier i in use thinks the selected action belongs to (binary in this case, either a or b) and $\alpha_{A,i}$ is a number between 0 and 1. The higher the value of $\alpha_{A,i}$ the more confident the classifier is (thus the degree of certainty). Decisions from all the 45 classifiers are used to score each class as follows :

$$score_A = \sum_i \alpha_{C,i} \delta_{A,C}$$

Finally to make a decision on which activity a sampled feature has been taken from, the following two approaches have been implemented and used in our model:

- predict the class that has the highest score (H_{score}) or
- put the output of every classifier and their corresponding score into a 3 layer (64,64,6) neural network (NN), for the final output .

The neural network use a Multi-Layer Perceptron (MLP) as the baseline classifier, making it possible to estimate accurate posterior probabilities. We used a three layer network topology with an input layer, a single hidden layer and six output layer, in which an MLP is used for recognising the six activities. The neurons of the input and the output layers are fully connected to the neurons of the hidden layer, and the transfer function is the sigmoid function. Furthermore, the network is trained with a sequential gradient descent with momentum applied to a sum-of-squares error function.

IV. EXPERIMENTAL RESULTS

For unbiased comparison, the UCI open repository has bee used to test our approach and compared with six other classification results presented in [8][20][22] from 2012 to 2017. The dataset was randomly split into a training set (of 75%) and a validation set (of 25%). In order to preset the parameter C for the SVM-based approach, the process of randomly splitting the data was repeated 200 times and the optimal value for C was chosen to be 0.1; similar to the predefined value in [22]. The confusion matrices in tables III and IV are the average scores after repeating 50 times for the two decision making approaches used (H_{score} and NN), using the validation set of 2958 instances. The following abbreviated labels have been used in tables III and IV: LA-Laying, SI-Sitting, ST-Standing, WA-Walking, UP-Walking upstairs, DO-Walking downstairs, ACT - Activity, PRE - Precision and ACC - Accuracy.

Table III
CONFUSION MATRIX FOR THE SCORING BASE APPROACH.

Proposed method with scoring decision							
ACT	LA	SI	ST	WA	UP	DO	ACC(%)
LA	537	0	0	0	0	0	100
SI	0	464	24	0	0	0	95.1
ST	0	26	510	0	0	0	95.2
WA	0	0	0	490	1	11	97.6
UP	0	0	0	9	405	0	97.8
DO	0	1	0	6	14	460	95.8
PRE(%)	100	94.5	95.5	97.0	96.4	96.7	96.9

Table IV
CONFUSION MATRIX FOR THE NEURAL NETWORK BASE APPROACH.

Proposed method with neural network							
ACT	LA	SI	ST	WA	UP	DO	ACC(%)
LA	521	0	0	0	0	0	100
SI	0	471	31	0	0	0	93.8
ST	0	12	502	0	0	0	97.7
WA	0	0	0	483	7	1	98.4
UP	0	0	0	15	394	8	94.5
DO	0	0	0	0	4	459	99.1
PRE(%)	100	97.5	94.2	96.9	97.3	98.1	97.3

The comparison of the correct accuracy of classification rate between different methods reported previously in literature is presented in table V. To reiterate, even though the one-versus-all polynomial approach presented in [8] performs slightly better than the proposed (H_{score} and Neural Network), the implementation in [8] is not hardware friendly and will require more effort to parallelise the classifier. This is mainly because of the use of polynomial kernel in [8] which requires a number of floating-point multiplications and would consume significant amount of FPGA resources when mapped onto such a parallel platform.

Table V
COMPARISON CORRECT ACCURACY CLASSIFICATION RATE BETWEEN DIFFERENT METHODS OF CLASSIFICATION OF TEST DATA.

Ref	Method	Accuracy(%)
[22]	$k-$NN	90.63
[22]	OVA SVM	93.72
[22]	OVO SVM Linear	96.40
[20]	OVA SVM Gaussian	96.50
Proposed	High Scoring (H_{score})	96.90
[8]	OVA Linear	96.91
Proposed	Neural Network (NN)	97.30
[8]	OVA Polynomial	98.57

V. Conclusion

The scoring decision method present here achieved an accuracy of 96.90% and the neural network decision approach achieved a remarkable accuracy of 97.30%, all based on the one-versus-one ensemble voting. It may be explained by the fact that the neural network can adapt the weight of each one-versus-one classifier presented in this work. Moreover this method can easily separate the groups presented in section III-A and most of the classification errors are rather within the groups. Furthermore the hardest group to separate is the sitting and standing even if it contains only 2 classes, it represents 54.30% of the overall errors for the first method, and 55.10% for the second method. The result obtained is an improvement of the base work presented in [22] implemented with SVM one-versus-one. In order to further improve the results, detailed analysis of the features can be conducted to select the best representative features for a one-versus-one classifier; which also eliminates the complexities of training with very large data as required in one-versus-all SVM classifier. The total training time when one-versus-one strategy is used can be reduced significantly by training all the binary classifiers in parallel on FPGA with much smaller training data rather than very large data, that will be a bottleneck for FPGA implementation. Now that the concept of activity recognition with accelerometer data is proven, work is ongoing to implement it on a parallel architecture like FPGA and also collect more data from people aged over 60, just to make the system robust for assistive care.

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